EARLY DETECTION AND CLASSIFICATION OF DIABETIC RETINOPATHY USING HYBRID DEEP LEARNING TECHNIQUES

SHORT SYNOPSIS

Submitted in partial fulfillment of the requirement of the degree of

DOCTOR OF PHILOSOPHY

by

Neeraj Singh Attri
Reg. No. MRUCSDN012K230004

Under the supervision of

Dr. Urmila
Associate Professor

Department of Computer Science and Technology

School of Engineering

MANAV RACHNA UNIVERSITY
Sector-43, Aravali Hills, Faridabad

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MANAV RACHNA UNIVERSITY
Sector-43, Aravali Hills, Faridabad

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DECLARATION BY THE SCHOLAR

I hereby declare that the short synopsis entitled "**Early Detection and Classification of Diabetic Retinopathy Using Hybrid Deep Learning Techniques**" being submitted in partial fulfillment of the requirement for the degree of Doctor of Philosophy in the Department of **Computer Science and Technology** under the School of **Engineering** of Manav Rachna University, Faridabad during the academic year **2024-25**.

It is the work that is expected to be carried out under the supervision of **Dr. Urmila**.

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Neeraj
12/06/2025

(Neeraj Singh Attri)
Reg. No. MRUCSDN012K230004

MANAV RACHNA UNIVERSITY
Sector-43, Aravali Hills, Faridabad

Date: 12-06-2025

CERTIFICATE BY SUPERVISOR

This is to certify that, the short synopsis entitled "**Early Detection and Classification of Diabetic Retinopathy Using Hybrid Deep Learning Techniques**" is an original piece of work done by research scholar **Neeraj Singh Attri** under the supervision of **Dr. Urmila** for the degree of Doctor of Philosophy in the Department of **Computer Science and Technology** under the School of **Engineering** of Manav Rachna University, Faridabad during the academic year **2024-25**.

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Urmila 12/6/25
Supervisor
Dr. Urmila
Associate Professor

ABSTRACT

In recent years, significant research efforts have been dedicated to assisting ophthalmologists in detecting and diagnosing eye diseases, especially Diabetic Retinopathy (DR). These studies primarily utilize Optical Coherence Tomography (OCT) and conventional imaging methods to capture essential indicators like retinal nerve fiber layer thickness and visual field data. Deep learning has introduced innovative models for DR detection, utilizing classification algorithms to enhance diagnostic accuracy. This research explores the development of effective diagnostic techniques designed for use in primary care settings to screen patients for signs of Diabetic Retinopathy. Patients identified with early signs can then be promptly referred to specialists, facilitating timely intervention. The proposed methodology leverages a Hybrid CNN that combines techniques like data augmentation, region-of-interest detection (using R-CNN or Fast R-CNN), and attention mechanisms to capture complex retinal image patterns carried out by transformers. By incorporating both pre-trained CNN models and domain-specific adjustments, this model aims to improve diagnostic accuracy and robustness. Performance will be assessed using inclusive metrics with precision, recall, F1-score, and accuracy, based on the confusion matrix. This approach promises an effective, efficient solution for early DR detection, with the potential to significantly enhance patient outcomes.

Keywords: Eye Disease, Ophthalmologists, Diabetic Retinopathy, Image Processing, Deep Learning, Neural Networks, Convolutional Neural Networks, Transformers.

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INTRODUCTION

Diabetic retinopathy (DR) is a condition resulting from high blood glucose intensity due to inadequate insulin generation in body. It significantly impacts the quality of life of affected individuals and primarily damages the retina, as well as the heart, nerves, and kidneys [1]. Retinopathy is an eye disease that affects the retina, the layer of light-sensitive cells at the backside of the eye that is necessary for visualization according to Figure 1 retinopathy can have different causes and degrees of severity, but in general, it is characterized by changes in the retina that can affect vision [2][3][4].

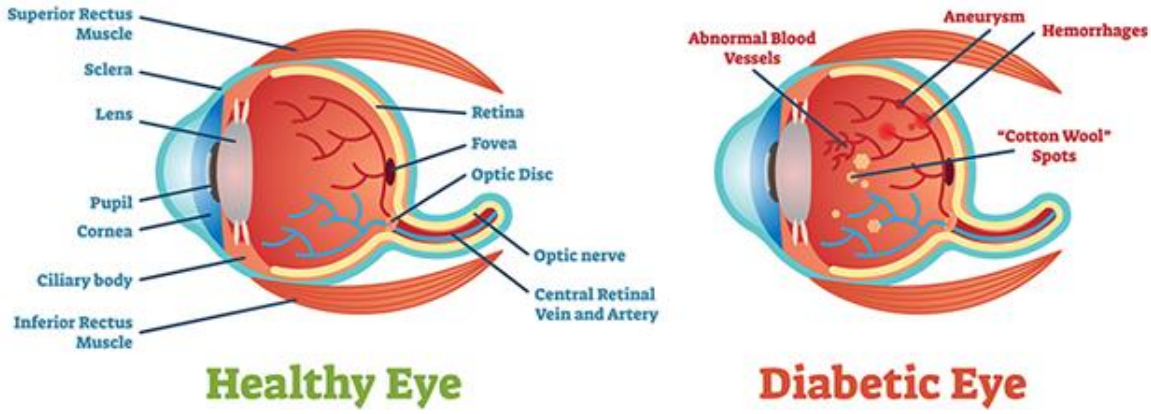

Figure 1: Eyes With and Without Retinopathy

With the periodic progression of DR, lesions, and abnormalities appear in the fundus of the eye, the detection of which allows different phases of the disease to be identified. Among the most common retinal lesions from the rupture of retinal blood vessels are: MAs, HEs, EXs, and CWs. Each of them is explained in more detail below [5-14]

1- Micro Aneurysms (MA): Localized capillary dilations, red and with a saccular structure. They can appear in groups or isolatedly, their number and extent depend on the phase of the disease. However, they typically have dimensions between 10 and 100 μm, which is why they appear as small round spots on fundus images.
2- Hemorrhages (HE): Structural distortions in the walls of the blood vessels of the retina that cause blood to leak through them. They have very different shapes, ranging from round red dots with clear margins to more indefinite fire-shaped dots.

3- Hard Exudates (EX): Small bright yellowish-white intra-retinal deposits with well-defined boundaries containing extracellular proteins and lipids as a result of blood leakage from abnormal retinal capillaries. These are some of the clinical signs used in grading DR. Grading includes:

   Grade 0: No apparent retinopathy. It is the first grade considered in the scale and refers to those cases in which there is no injury or relevant change in the fundus of the diabetic patient's eye.

   Grade 1: Mild RDNP. It is considered the earliest period of the illness and is illustrated by the occurrence of some MAs in the retina.

   Grade 2: Moderate RDNP. This is the second stage of the disease and in it, the appearance of more lesions apart from AMs is observed, such as intra-retinal HEs.

   Grade 3: Severe RDNP. The third degree of the illness is illustrated by the existence of any retinal lesion already mentioned. Also, at this stage, Intraretinal Microvascular Anomalies (IRMAs) can be observed.

   Grade 4: RDP. It is the higher juncture of the disease and is distinguished by neovascularization of the core formation of the eye such as the optic disc (OD), retina, and IRIS.

4- Algonodous exudates (CW): Irregular cloudy spots with diffuse or poorly defined limits and larger than EXs. They are usually whitish or grayish and appear as a consequence of local ischemia that leads to interruption of axoplasmic flow.

Numerous traditional techniques have been employed by researchers to identify DR in retinal or fundus images. However, these approaches are often time-consuming, depend on human intervention, and deliver lower accuracy compared to modern automated techniques. A significant step in the early identification and management of DR is the automated detection of retinal abnormalities. To support this, numerous methods have been initiated for the segmentation and identification of DR-related features and anatomical landmarks. The integration of deep learning (DL) with ophthalmic imaging, combined with the rapid and unprecedented advancements in DL, has opened up new and promising avenues for research in this field.

The proposed Hybrid CNN model integrates techniques such as data augmentation, region-of-interest detection (using R-CNN or Fast R-CNN), and attention mechanisms implemented through transformers to effectively capture complex retinal image patterns. By combining pre-trained CNN architectures with domain-specific enhancements, the model is designed to improve diagnostic accuracy and robustness. Its performance will be estimates via metrics, inculcated using F1-score, recall, precision and accuracy, derived from the confusion matrix. This technique proposes promising, proficient results for before time detection of DR, with the probable to significantly recover patient swiftly.

LITERATURE REVIEW

The literature review has been done to find the gaps in existing work and based on those gaps problem statement is formulated. The output obtained passes through a feed-forward network, that is, a perceptron in which the connections between the neurons are unidirectional, to obtain a better representation. The outputs are normalized again and the residues of the previous layer are added in this way to the output of the encoder along with the inputs. From the previous steps they pass to the decoder where they follow a mechanism very similar to that described for the encoder to give the corresponding output probabilities for each of the initial inputs as a final result. Two main groups of algorithms can be distinguished for the detection of DR using CNNs: those that try to detect the characteristic lesions of DR and those that directly detect and classify the disease. An example of the first type would be the study by [20], in which a DL system was developed for the detection of lesions such as EXs, MAs and HEs. In this, first an evaluation of the quality of the images was carried out, which was divided into three categories for validation (sharpness, position and artifacts). Only images whose quality scores met certain standards were included in the study.

Based on image processing techniques computing resources, as well as digital imaging techniques, have improved rapidly and have found more and more practical applications. In the field of ophthalmology, in the last 20 years, researchers have used digital image processing techniques for screening and detecting diseases, since they simplify the diagnosis, making the work of ophthalmologists easier. Regarding the obtainable techniques in the literature to identify ocular pathologies or conditions using this type of technique, most of them focus on diagnosing diabetic retinopathy as under:-

In [21] an investigation was carried out on the recognition of HEs using a hybrid scheme in color fundus images. For this, the 3D Gaussian algorithm and the method recognized as CLAHE were used to enhance the contrast of the fundus images. Extraction of bleed candidates was performed using a rounded pattern with Normalized Cross-Correlation (NCC). In [22] combined circular convolution and residual connection to replace the original submodule of the U-Net model, and their detection accuracy reached 99.18%. This method effectively overcomes the gradient disappearance problem in the model

training stage while enhancing feature expression. The above improvements introduce attention modules, context extraction modules and circular convolution to obtain more comprehensive lesion features and refine the detection results, but the structure cannot increase the connection between network modules, so the number of data flow paths does not change.

This is the case of the method proposed in [23] in which the two previous types of lesions are detected. His main contribution was the use of a new set of shape characteristics, called DSF, which did not require precise segmentation of the regions to be classified. The best results were obtained when images without DR were classified versus images with all stages of DR. In this context, the proposed method obtained an area under the ROC, commonly known as AUC, of 0.90, a sensitivity of 93.90%, and a specificity of 50%. In the case of PDR, it is also possible to find neovascularization.

In [24] the automated recognition of new blood vessels from retinal imagery was carried out. Vessel segmentation was performed by applying two approaches, the customary line operative and a new customized line operative. Finally, an autonomous categorization was carried out for each set of features using an SVM classifier. For the diagnosis of optic nerve head pathologies such as glaucoma, OD segmentation is an crucial step to create a frame of reference. With respect to this disease, there are a variety of eye parameters widely used for its diagnosis. Some of the most relevant are the following: the Cup-Disc Ratio (CDR), the Neural Edge of the Retina (NRR), the diameter of the cup, the blood vessels of the Inferior, Superior, Nasal, and Temporal region (ISNT) and Peripapillary Atrophy (PPA) [25].

About the latter, PANDORA was proposed in [26], a system that allowed the automated detection and quantification of PPA and OD regions in fundus images. In the study by [27], the segmentation of the OD and the optic cup was necessary to create a versatile procedure based on thresholds that would improve the identification and grouping of said ocular pathology. In this case, for the final classification, an SVM classifier with several kernels was utilized. The method proposed in [28] uses image processing techniques to classify retinographies into three different classes: normal, cataract, and post-cataract. To do this, a system similar to the previous ones was created, although the characteristics

that were extracted were different. Finally, an SVM classifier was used to determine which class each image belonged to. The results obtained were clinically significant since the technique attained an normal precision of 88.39%, a sensitivity of 94%, and a specificity of 93.75%.

For the diagnosis of DR, the presence of exudates in the retina is the most characteristic symptom of the disease. These clinical signs are also known as bright lesions and are usually detected in the early stages, which is why they are of vital importance for the task of mass screening and follow-up of DR [29]. Researchers in [30] combined circular convolution and residual connection to replace the original submodule of the U-Net model, and their detection accuracy reached 99.18%.

In [31], developed a model to classify retinopathy based on microaneurysms and exudates using DIARETDB0 and DIARETDB1 datasets. In this study, Wavelet and SVM methods were applied. The results showed that the Weighted KNN method achieved an accuracy of 85.8%, while the Cubic method using the slope feature and level 5 wavelet achieved the highest accuracy. Meanwhile, the One-Against-All multiclass SVM achieved an accuracy of 72% using the slope parameter, indicating that advanced image processing techniques can improve the accuracy in diagnosing retinopathy. This study provides a strong foundation in the use of advanced image processing techniques for the diagnosis of eye diseases, especially retinopathy.

In [32], utilized the MESSIDOR dataset and applied an ensemble learning approach with a combination of Random Forest, Neural Network, and SVM algorithms. This study aims to improve the accuracy of eye disease detection by utilizing the strengths of various models. Using two feature selection methods, namely InfoGainEval and WrapperSubsetEval, the results show that the accuracy reaches 70.7% with InfoGainEval and increases to 75.1% with WrapperSubsetEval. This study highlights the importance of selecting the right features and combining various algorithms to improve model performance in eye disease classification tasks, which serves as a reference in developing more complex and accurate models.

In [33], conducted a study using the Kaggle dataset consisting of 3,662 fundus images. Of these, 2,930 images were used for training and 732 images for validation. This study used the CNN U-Net model and applied various data augmentation techniques such as rotation, zoom, flip, blur, brightness, and saturation to improve data variation and model performance. In addition, Gabor filtering was used to detect frequency-specific pixels to clarify the nerve lines in the fundus images. Opening morphological transformation was used to reduce noise in the final image. As a result, this neural network successfully achieved a specificity of 0.94 and an accuracy of 0.83 in detecting Diabetic Retinopathy (DR), demonstrating the effectiveness of this comprehensive approach. This study provides an important foundation in the development of data augmentation and image processing techniques to improve model accuracy in diagnosing eye diseases..

In [34], used the APTOS 2019 dataset consisting of 3,662 training images, as well as the Kaggle 2015 dataset consisting of 35,126 retinal scan images. In this study, data fusion techniques were applied to predict Diabetic Retinopathy (DR) using the DenseNet model. The DenseNet architecture with feature fusion was applied to improve DR detection, supported by advanced clinical image processing and detection techniques. The results showed that this model successfully achieved a training accuracy of 93.51%, with a precision and recall of 0.98, indicating the effectiveness of data fusion techniques in improving model performance in DR detection. This study provides a strong foundation for the development of models with feature fusion techniques in the diagnosis of eye diseases.

Recent research by Vardhan, et al., in 2024[35], used the MESSIDOR dataset consisting of 400 retinal image data categorized into No DR and DR. This dataset was then adjusted for binary and multi-class CNN classification. In this study, the model used was a combination (hybrid) of InceptionResnetV2 and DenseNet121. The results showed that the InceptionResnetV2 model successfully achieved a training accuracy of 0.9782, a testing accuracy of 0.9421, and a training AUC of 0.9968. On the other hand, the DenseNet121 model achieved a training accuracy of 0.7911, a testing accuracy of 0.7511, and a training AUC of 0.8466. This study shows that the combination of two powerful architectures can produce excellent performance in the classification of eye diseases

based on retinal images. This study also underlines the importance of integrating various techniques and models in improving the effectiveness of image-based diagnosis in the health sector.

In [36] aims to show the impact of implementing SOP on DR data processing, using the ResNet-50 model on the EyePACS dataset. This study provides a standard procedure that can be carried out at the preprocessing stage of fundus images. The stage begins by removing the black area on the fundus image. Then, a circular cropping will be carried out on the image. After that, a quality check will be carried out on the fundus image. Images with appropriate quality will be reprocessed using histogram equalization to clarify the image. The Revised ResNet-50 model proposed in this study provides a test accuracy of 74%. The suggestion given in this study is to conduct further analysis on different CNN models using transfer learning and hyperparameter-tuning to improve classification performance.

In [37] used a transfer learning approach on the VGG-16 model to detect DR. Experiments were conducted repeatedly by changing the number of categories of the DR level. Based on the evaluation results, the model created without augmentation was able to provide better accuracy results. However, the model provided overfitted results. In addition to VGG-16, this study also tested other models, namely ResNet50 and Inception. The three models provided the same accuracy results of 75% in the five-class DR classification. Based on the test, it was found that the boundaries between different classes were not very clear, especially between mild and normal, and between severe and proliferative classes. This study suggests finding a more accurate technique or model in distinguishing DR levels.

Transfer learning is also used in the study [38]. Transfer learning is used on the trained Inception-ResNet-v2 model, then a custom CNN block is added to build a hybrid model. The model is then evaluated on the Messidor-1 and APTOS 2019 datasets. The model created provides 6.3% greater accuracy compared to the GoogLeNet model. On the Messidor-1 dataset, the model provides an accuracy of 72.33%. While on the APTOS dataset, the model provides an accuracy of 82.18%. The suggestion from this study is to

balance the data distribution and conduct further research on transfer learning to improve overall performance.

In [39] used CNN architecture and transfer learning method using GoogLeNet and VGG-16 models. This model was trained using EyePACS data totaling 88,702 images. The results of the experiment when using the GoogLeNet model with the Sigmoid function as the activation function and a learning rate of 0.01 gave an accuracy of 61.58%. The VGGNet-16 model with fine tuning gave an accuracy of 71.65%. This study suggests using new techniques to improve accuracy by considering the training time. Experiments can also be done on blue or red images as input to the model.

Based on the above studies that are explored, some significant research gaps are listed in Table 1:

Table 1 Literature Review Table

Area	Problem	Gap	Suggested Research
Early Detection and Progression Prediction [21][22][23][24][25][29][52]	Current deep learning models focus largely on detecting DR once it has already progressed to noticeable stages.	There is inadequate exploration focusing on quick recognition and envisage the development of DR over time.	investigate secular models or integrate longitudinal patient data to forecast the progression of DR in its early stages using Hybrid DL models.
Multi-modality Data Integration [21][27][30][32][34][38][39][42][43]	Most DR detection models rely on fundus imaging, which captures only one aspect of retinal health.	Few studies integrate multi-modality data, such as OCT, patient clinical history, and other biometrics.	Combining data from multiple imaging modalities and patient histories using Hybrid Multi-modal Deep Learning approaches to improvise the

			accurateness of DR analysis.
Data Scarcity for Rare DR Stages [28][38][50][51][52][54]	Datasets are often imbalanced, with more images for common DR stages and very few for rare stages, like PDR.	Imbalanced datasets limit the ability of models to detect rare, yet clinically important, stages of DR.	Investigating methods like data augmentation, synthetic data generation, or transfer learning to deal with data scarcity for rare DR stages.
Segmentation of DR Lesions [24][27][53]	While many models focus on classification (i.e., detecting whether DR is present), fewer models focus on lesion segmentation, which is critical for detailed clinical analysis.	Accurate and reliable segmentation of microaneurysms, hemorrhages, exudates, and neovascularization remains a challenge.	Developing more accurate and fine-grained lesion segmentation models using advanced architectures like U-Net or transformers.
Lack of Generalization in Models [21][22][26][27][31] [32][35][36] [37][38][39]	Most DL models for DR detection and identification are trained/test/validated on inadequate data resources from precise demographics or hospitals.	There is a insufficiency in the models that simplify well across different masses, ethnicities, and imaging devices.	Improvement in models to facilitate and simplify transversely on various populations by integrating multi-center datasets with varied imaging technologies.

DESCRIPTION OF BROAD AREA

- **Deep Learning (DL)**

DL is a very extensive notion, which means that it does not have an exact definition, but studies [9, 10] have the same opinion that DL comprises a set of algorithms that challenges to form elevated level of concept, through the modeling of several dispensation layers. The great advantage of DL is not requiring data characterization for learning, on the contrary, the system recognizes without help how to capture the data to process them automatically. The machine can recognize patterns in the data input that are not perceptible to humans with the naked eye, due to their sensory limitations [15].

- *Artificial Neuronal Networks (ANN)*

DL models use ANN, which aim to imitate the biological model of the brain, through mathematical models organized in networks interconnected massively in parallel and with hierarchical organization [16]. These models offer advantages for solving problems, which has increased their application. Among the most significant advantages of neural networks are the presented by [17]:

- *Adaptive learning*. They are an ML model and therefore can learn and perform tasks based on initial experience. It receives data in the learning stage.
- *Fault tolerance*. Two types of fault tolerance are considered; network fault tolerance where, if a partial destruction of the network occurs, some capabilities can be retained. Second is fault tolerance regarding data where neural networks are capable of learning to recognize patterns in incomplete or noisy distorted data.
- *Real-time operation*. They support parallel computing, but the hardware must be designed to allow this capability.
- *Easy insertion*. Currently, there are specialized chips for artificial neural networks that allow us to improve the capacity of certain tasks applied by these models.

- **Convolutional Neural Networks (CNN)**

CNNs are a type of multilayer NN. They are focused on the fields of CV and NLP. A CNN is made up of a set of one or more convolution and pooling layers as shown in Figure 2, followed by one or more fully connected layers, and an output layer. The basis of the convolutional network is the set of layers [18].

- Convolutional Layer: This layer contains a series of kernels or filters that will be applied to the input data. The output of this layer generates a map with the features that serve as input for the next layer of the neural network.
- Kernel: The kernel is a matrix of discrete values; each value in the matrix can be described as a weight of the kernel. During the training process, the kernel learns to extract useful information from the input data.
- Pooling Layer: The pooling layer, as shown in Figure 2, is used to reduce the size of the feature map. In a similar way to the convolution layer, a kind of filter is applied that maps the input matrix and applies an operation on each segment of the matrix. The operations that can generally be applied are the maximum, the average, or the sum.
- Fully Connected Layer: This layer is equivalent to the hidden layer of a normal neural network. The results of the previous layer are linked to all the neurons or units of the next layer.
- Softmax Activation Function: This step is used to perform classification. It generates results that represent potential outcomes, which may not yet be standardized within each class.

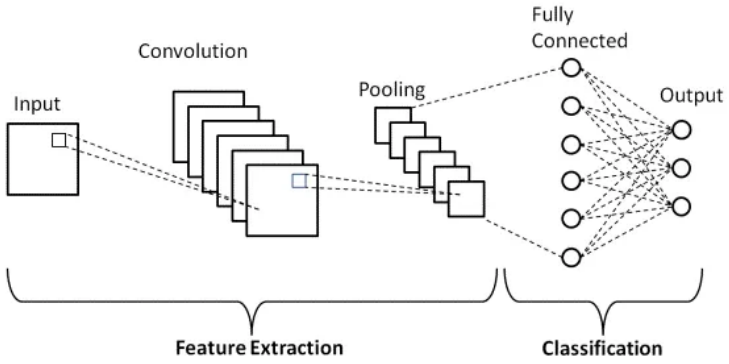

Figure 2: Representation of the architecture of a CNN [18].

- **Faster-Region Based CNN (RCNN)**

Faster-RCNN is born from the modification of networks pre-existing. In this case, we can start from the RCNN a neural network that extracts about 2000 Regions of Interest (RoI) and analyzes them separately in order to classify them [19]. The model of RCNN is shown in Figure 3.

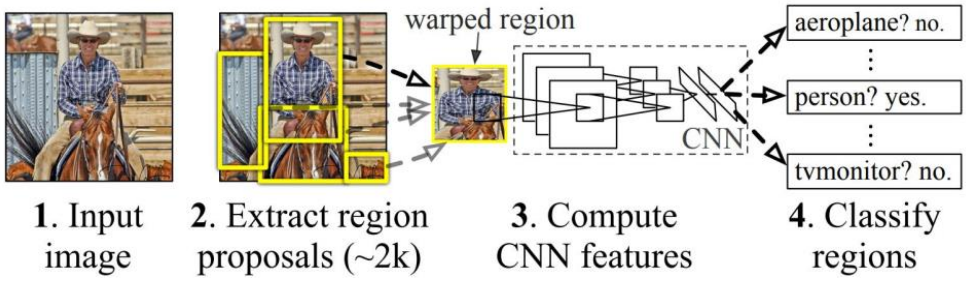

Figure 3: Architecture of a RCNN [19]

The biggest problem with this network is that the prediction for each new image takes between 40 and 50 seconds, implying that using large databases to train it entails a large investment of time. So, is there a way to improve these times?

The possibility of collecting all the RoIs in a pooling layer could be considered, where they are given a common size before entering the classifier. Thus, Fast-RCNN is introduced in Figure 4.

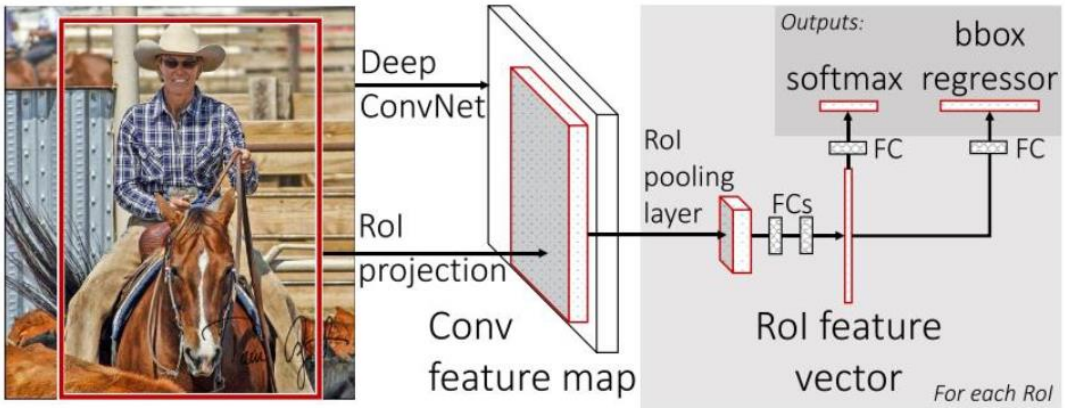

Figure 4: Architecture of a Fast-RCNN [19]

The advantage provided by Fast-RCNN comes from the added pooling layer since this allows computing the 2000 regions simultaneously instead of sequentially. However, despite taking much less time than an RCNN, it takes 2 seconds for the classification of a single image [19].

- **Visual Transformers**

To correctly understand the operation of ViT, it is necessary to understand the operation of its main element, the transformer. This type of architecture was developed in order to improve the limitations that the Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU) units presented when taking into account the temporal relationship between

the different variables [20]. The differentiating element of the transformer is found in its architecture, created to get rid of the recurring systems that the previously mentioned models made use of. To do this, they used self-attention mechanisms. Figure 5 shows a diagram of the Transformer architecture.

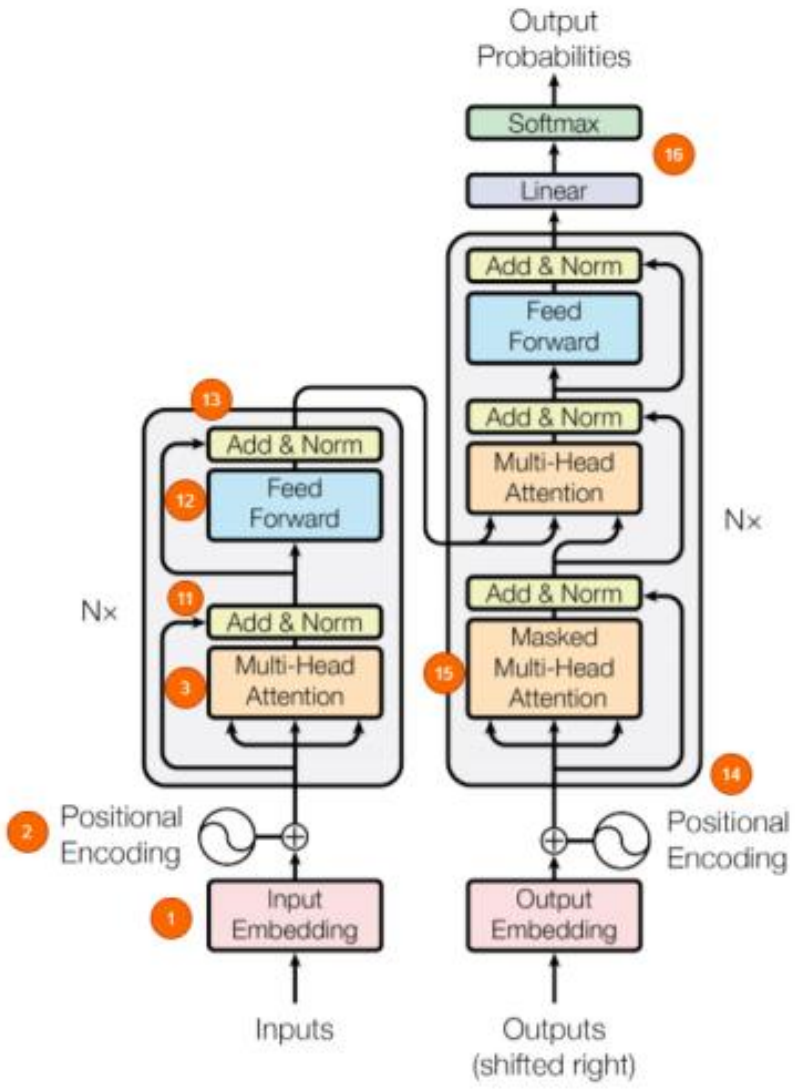

Figure 5: Architecture of a Transformer [20]

Broadly speaking, we can distinguish two main parts in its architecture: the decoder on the left side and the encoder on the right side of the diagram in Figure 5. The encoder is responsible for taking the input and generating from it an intermediate representation that will later be decoded by the decoder. This, in turn, will be responsible for generating the corresponding output. Explaining this process in greater detail, the input data are

integrated into a vector thanks to the superimposed layer or embedding layer, allowing a vector representation to be obtained for each unit of information [20]. In the next stage, a positional encoding is performed to represent the order of the sequence. To use the multi-headed attention mechanism. In it, shown in greater detail in Figure 6, three vectors (query, key, and value) are generated for each of the input vectors. From query and key, a score matrix is obtained that represents the relationship that each unit of information has with the rest, in such a way that the higher the score, the greater the relationship and vice versa. This scoring matrix is subsequently reduced to the dimensions of query and key to ensure the stability of the gradients [20].

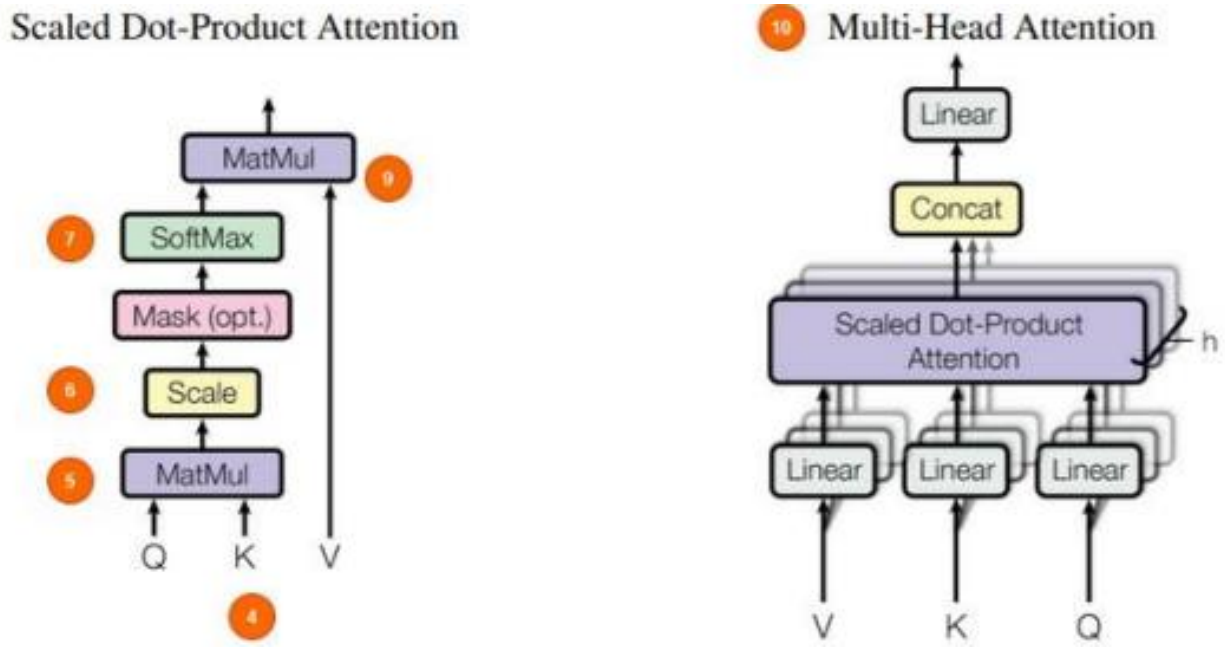

Figure 6: Multi-headed-attention architecture [20]

In the next stage of the process, the score matrix is subjected to a softmaxing process to convert the attention scores into probabilities. The resulting matrix is multiplied by the value vector, making the highest probabilities more important and those with lower scores considered irrelevant. This entire process is explained in detail in the Scaled Dot-Product Attention, whose inculcated output of the query, key, and value vectors passes through a linear layer for subsequent processing. The self-attention mechanism is applied to each element considered as a unit of information by the network, in such a way that, as

they are independent of each other, a copy of the self-attention module is used to process everything simultaneously (multi-headed) [20].

RESEARCH OBJECTIVES

Based on the gaps obtained from the literature review four research objectives have been framed for the proposed research work:

RO1: To improve the existing DR detection algorithms for better accuracy and classification.

RO2: To resolve the problem of false positive detection using deep learning techniques.

RO3: To design and develop a novel Hybrid CNN Model for Early Detection of Diabetic Retinopathy.

RO4: To test and validate the proposed work it will be compared with state of art work using standard performance metrics.

RESEARCH METHODOLOGY

The proposed approach employs a hybrid deep learning framework integrating CNN, R-CNN, Fast R-CNN, and transformer models to improve the early and automatic detection of DR using retinal fundus image datasets including Messidor and EyePACS. The details of the datasets have been given as follows:

1. EyePACS dataset [48]

The EyePACS dataset consists of 88702 retinal images collected from various clinics in various countries. This collection technique makes the EyePACS dataset have a large variation in data due to differences in the type of fundus camera in each clinic, operator capabilities and patients. As a result, many retinal images in the EyePACS dataset do not have good focus, have artifacts, and have inconsistent lighting, making them quite difficult to classify. The dataset consists of thousands of high-resolution retina (fundus) images, which capture the back of the eye. Each image in the dataset has been labeled with a DR severity grade, ranging from 0 to 4:

0:.No

1:.Mild

2:.Moderate

3:.Severe

4:.Proliferative

Labeling: The grading process was conducted by certified human graders, often ophthalmologists, to ensure accuracy.

2. Messidor Diabetic Retinopathy Dataset [49]

The Messidor dataset is one of the most commonly used public datasets for DR recognition and grading. Although it has less data than the EyePACS dataset, this dataset does not have a large variation in image quality, because the image acquisition process is carried out by only one institution. Thus, more physiological variations can be found than

image quality variations, which can make the model learn lesions in DR more easily. The repository consists of 1,200 color fundus photographs.

Labels: The dataset provides grading annotations for each image:

0: No DR

1: Mild non-proliferative diabetic retinopathy (NPDR)

2: Moderate NPDR

3: Severe NPDR

Additionally, each image is graded for the risk of macular edema using a binary scale (0 or 1), where:

0: No risk of macular edema

1: Presence of macular edema

Dataset Size: 1,200 retinal images divided into three sets by different research centers, allowing for training, testing, and validation. The dataset has been used to apply CNN, R-CNN, Fast R-CNN, and Transformer models. Each model is explained below:

CNN Module: The initial stage uses CNNs to extract fundamental visual features from retinal images. These include low- to mid-level patterns like edges, textures, and color gradients that help highlight retinal structures. These features are essential for identifying clinical signs of DR such as microaneurysms, hemorrhages, and abnormal blood vessels [40].

R-CNN and Fast-RCNN: In the next stage, the R-CNN and Fast-RCNN-based components identify ROIs within the image, concentrating on areas likely to contain DR-related lesions. By isolating and analyzing these regions, the model becomes more sensitive to minor abnormalities and subtle indicators of disease progression [41].

Transformer Module: To further enhance understanding, a transformer module is incorporated to model long-range dependencies and contextual relationships between extracted features. The self-attention mechanism in transformers helps the model focus on important regions within the fundus image, particularly beneficial when lesions are sparse or not clearly defined [44].

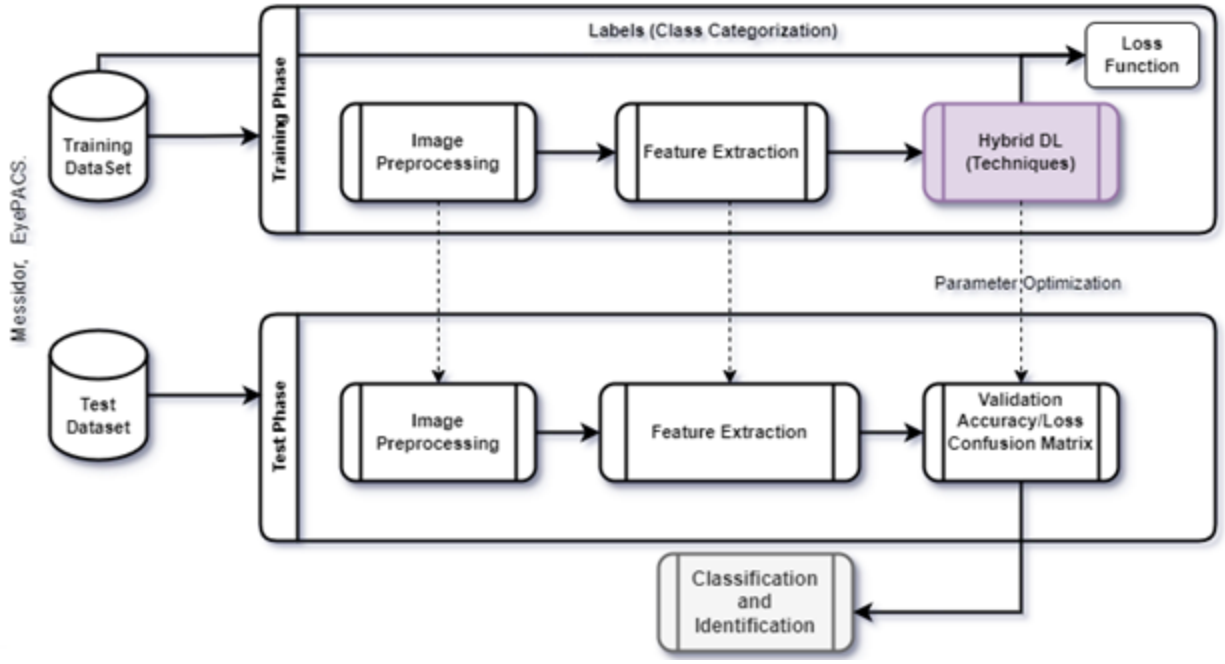

Figure 7: Proposed Model Flow Chart

An overview of DR Classification and Identification is shown in Figure 7.

Stage 1: CNN Feature Extraction

- Sequential convolutional layers extract low-to-high-level features.

Stage 2: Fast R-CNN Region Proposal and Classification

- Regions of interest are identified, targeting DR-specific areas (e.g., hemorrhages, exudates).
- These regions are classified into DR stages (No DR, Mild, Moderate, Severe, Proliferative).

Stage 3: Transformer Attention Module

- Adds self-attention across regions to emphasize spatial dependencies and context.
- Helps model nuanced patterns, improving DR classification accuracy.

Performance Evaluation: An important tool for visualizing model performance predictive is the Confusion Natrix (CM). The rows of this matrix represent the number of predictions for each class and the columns represent the actual value of the class. This will provide important information about whether the model is classifying correctly each class in research. Figure 8 shows an example of the mentioned matrix [45][46] [47].

	Class Value		
Prediction Value		+	−
	+	True Positive(TP)	False Positive(FP)
	−	False Negative(FN)	True Negative(TN)

Figure 8: Confusion Matrix

Where TP is the number of illustrations that have been classified correctly as positive. TN is the amount of illustrations evaluated correctly as negatives. FP is the amount of illustrations evaluated erroneously as positive, also called Type 1 Error and FN is the amount of illustrations wrongly classified as negative, also called Type 2 Error.

- **Sensitivity**

This metric will provide the true positive TP rate among all true positive cases, that is, the probability that X-rays whose binary attribute of consolidation-stage (first-stage) pneumonia will be medically diagnosed as positive. The goal is for the value of this metric to be as close to 100% as possible, since the higher the value, the more sensitive the diagnosis, so this metric must be used when the false negative rate FN is high [55]. The sensitivity as shown in Equation 1 will be used for the measurement of results in the proposed methodology:

$$\boldsymbol{Sensitivity = \frac{TP}{TP + FN}} \qquad (\mathbf{1})$$

- **Specificity**

This metric will provide the rate of the sample identified as correctly negative TN. What the probability of radiographic images with the normal binary attribute will mean is diagnosed as negative. In the same way as the sensitivity, this value should be the most close to 100% possible to make the result more accurate [55]. The specificity as shown in Equation 2 will be used for the measurement of results in the methodology:

$$\boldsymbol{Specificity = \frac{TN}{TN + FP}} \qquad (\mathbf{2})$$

- **Accuracy**

Accuracy will measure all correctly identified cases. This metric finds the relationship between the y number of true samples, which means true positive and true negative with the total number of samples [55]. The precision as shown in Equation 3 will be used to measure results in the proposed methodology:

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TN} + \boldsymbol{TP}}{\boldsymbol{TN} + \boldsymbol{FP}} \qquad (\mathbf{3})$$

Results: The Results from these modules are combined using a proposed strategy to produce the final DR severity grade. This hybrid approach leverages CNNs for feature extraction, R-CNNs for precise region identification, and transformers for high-level context understanding, resulting in a model that is both accurate and robust.

EXPECTED OUTCOME

The proposed methodology for detecting and classifying diabetic retinopathy using a hybrid CNN is designed to enhance the accuracy and robustness of diagnosis by leveraging both pre-trained CNN models and domain-specific customizations. By employing techniques such as data augmentation, RoI, and attention mechanisms forming hybrid architectures (e.g., combining CNN with Fast-RCNN or Transformers), the model can effectively capture complex patterns in retinal images. The use of weighted loss functions addresses class imbalance, while metrics like precision, recall, F1-score and accuracy ensure comprehensive performance evaluation. This approach promises an effective solution for early detection and classification of diabetic retinopathy, potentially improving clinical outcomes.

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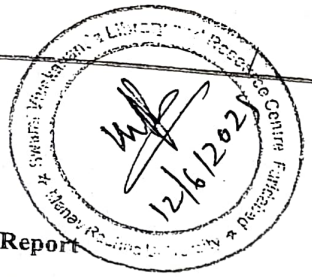

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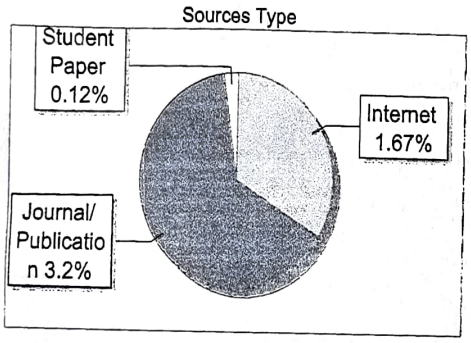

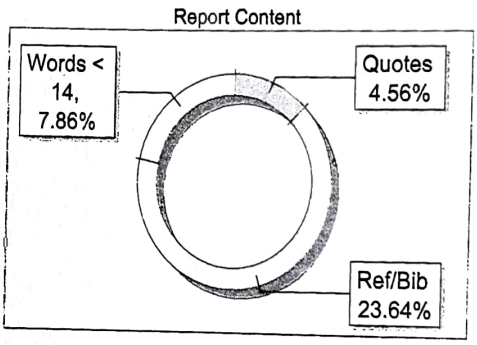

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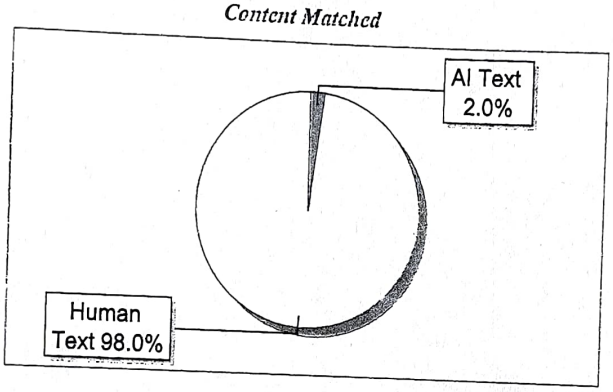

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